Health Management System Design: Development, Simulation and Cost/Benefit Optimization[1]

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Abstract—This paper provides an update to [1] on the developments associated with a Prognostics and Health Management (PHM) system design tool that integrates a model-based FMECA methodology with state-of-the-art system simulation directly linked to downstream Life Cycle Costs (LCC). This design tool will seek out recommended PHM system designs based on a cost function that accurately represents key LCC variables such as system availability, maintainability, reliability, and failure mode observability. The tool will be capable of assessing PHM sensor requirement specifications at the component and subsystem levels, and will then allow for integration into a broader integrated system model. Tradeoff, sensitivity and "what if" analysis will then allow the designer/user to examine the cost/benefit relationship of either adding or removing sensor and algorithms under consideration for the PHM design. An interactive database of existing PHM technologies for specific applications will also be accessible within the design tool for suggesting sensors/algorithms for monitoring various system parameters. Finally, the approach introduces a collaborative, web-enabled environment for enhanced realization and virtual simulation of PHM system design. A simplified example of a Health Management system cost/benefit analysis on an aircraft electromechanical valve is provided for illustration of the concepts introduced.

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1. INTRODUCTION

The application of "health" or "condition" monitoring systems serves to increase the overall reliability of a system through judicious application of intelligent monitoring technologies. A consistent health management philosophy integrates the results from the health monitoring system for the purposes of optimizing operations and maintenance practices through, 1) prediction, with confidence bounds, of the Remaining Useful Life (RUL) of critical components, and 2) isolating the root cause of failures after the failure effects have been observed. If RUL predictions can be made, the allocation of replacement parts or refurbishment actions can be scheduled in an optimum fashion to reduce the overall operational and maintenance logistic footprints. Fault isolation is a critical component to maximizing system availability and minimizing downtime through more efficient troubleshooting efforts.

Aside from general exceedence warnings/alarms, health monitoring initiatives mostly take place after in-field failures (and substantial costs) have been incurred. To address this issue, this paper proposes the concept of a Health Management Virtual Test Bench or a software tool that is not only used for health monitoring system design but also for system validation, managing inevitable changes from in-field experiences, and evaluating system design tradeoffs (Figure 1).

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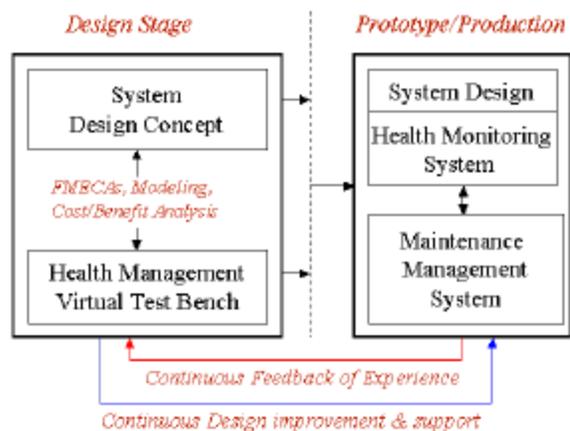| Classification of Abstract unclassified	Limitation of Abstract UU

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Figure 1 - Health Management with System Design

Because an initial system FMECA is performed during the design stage, it is a perfect link between the critical overall system failure modes and the health management system designed to help mitigate those failure modes. Hence, a key aspect of the process presented links this traditional FMECA analysis with health management system design optimization based on failure mode coverage and life cycle cost analysis.

2. ROLE OF FMECA IN HEALTH MANAGEMENT

FMECA's historically contain 3 main pieces of information as described below:

1. A list of failure modes for a particular component
2. The effects of each failure mode ranging from a local level to the end effect
3. The criticality of the Failure mode (I – IV), where (I) is the most critical

While this type of failure mode analysis is beneficial in getting an initial (though generally unsubstantiated) measure of system reliability and identifying candidates for redundancy, there are several areas where fundamental improvements can be made so that FMECA's can assist in health monitoring design. Four shortcomings of traditional FMECA's are:

1. Traditional FMECA does not address the precursors or symptoms to failure modes.
2. To move maintenance from reactive to proactive, it is important to focus on both system and component level indications that the likelihood of a substantial failure mode has increased. Failure mode symptoms that occur prior to failure are these indications. An example of failure mode symptoms associated with a bearing would be an increase in spike energy or an increase in the oil particulate count.
3. Traditional FMECA does not address the sensors and sensor placement requirements to observe failure mode symptoms or effects.

4. Traditional FMECA does not address health management technologies for diagnosing and prognosing faults.
5. Traditional FMECA typically focuses on subsystems independently.

With these shortcomings in mind, a new approach has been developed that extends far beyond traditional FMECA capability and used in the design of health monitoring and management systems.

3. APPROACH TO HEALTH MANAGEMENT DESIGN

Figure 2 provides an overview of the approach to health management system design optimization. A basic description of each block will be given first, then details associated with each block will follow. First, a Function Block diagram of the system must be created that models the energy flow relationships among components. This functional block diagram provides a clear vision of how components interact with each other across subsystems. On a parallel path, a tabular FMECA is created that corresponds to a traditional FMECA except it contains failure mode symptoms, as well as sensors and diagnostic/prognostic technologies. Alternately, a system response model may be used for assessing sensor placements and observability of simulated failure modes thus offsetting the manual burden of creating the FMECA. Finally, maintenance tasks that address failure modes are included.

The information from the Functional Block diagram and the tabular FMECA is automatically combined to create a graphical health management environment that contains all of the failure mode attributes as well as health management technologies. The graphical health management environment simply a sophisticated interface to a relational database. Once the graphical health management system has been developed, attributes are assigned to the failure modes, connections, sensors and diagnostic/prognostic technologies. The attributes are information like historical failure rates (failures / 1E5 operating hours), replacement hardware costs, false alarm rates etc., which are used to generate a fitness function for assessing the benefits of the health management system configuration. The "fitness" function criteria include system availability, reliability, and cost. Some of these attributes must be manually determined, if known, while others are related to the attributes of the diagnostic/prognostic technologies can be determined from independent measures of performance and effectiveness tests or from pre-developed databases. Finally, the health management configuration is automatically optimized from a cost/benefit standpoint using a genetic algorithm approach. The net result is a configuration that maintains the highest system reliability to cost/benefit ratio.
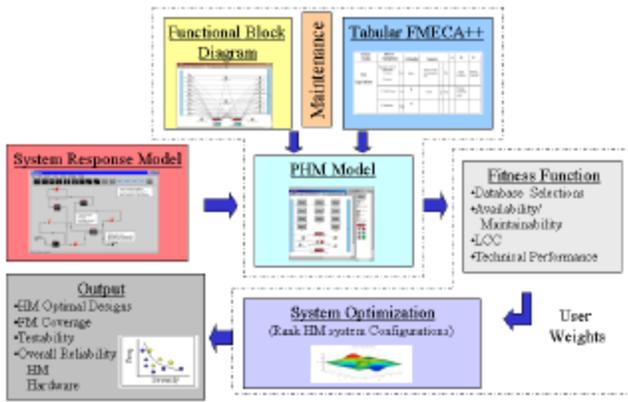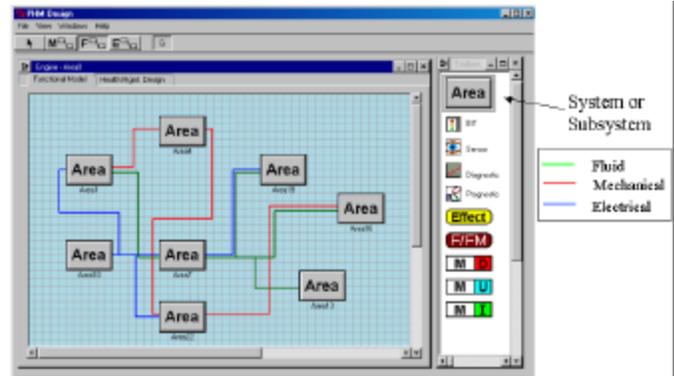
Figure 2 – Architecture of PHM Design tool

Figure 3 – Functional Block Diagram Layout

4. FUNCTIONAL BLOCK DIAGRAM

The Function Block Diagram (FBD) contains an integrated representation of how components, subsystems and systems interact with one another. It is not a simulation, only a hierarchical map of physical energy flows (i.e. torque transfer, current, pressure). This energy flow map serves as the backbone for the health management design environment because it contains the failure mode symptoms and effects as well as capturing their temporal paths. Figure 3 shows an example of a functional flow diagram at a "system" level. One could select any of the components to reveal specific interactions between its associated subsystem components.

5. ENHANCED FMECA

As previously mentioned, with this approach, traditional FMECA analyses were enhanced with the addition of sensors, health monitoring technologies and failure symptoms. Figure 4 shows an example of an enhanced FMECA performed on a portion of a fuel system for a F-100 engine created by Penn State ARL and Impact Technologies.

As with traditional a FMECA, the failure mode is provided along with its effects (ranked from top to bottom as primary, secondary, tertiary, etc.). The Criticality or Frequency of Occurrence of the failure mode is ranked from A to E where:

A = Frequent,
B = Probable,
C = Occasional,
D = Remote,
E = Improbable

Figure 4 – Tabular FMECA of a F-100 Fuel System

In practice, this Criticality letter would be associated with a specific probability of failure range.

The Severity of the failure mode is ranked from I-IV where:

I – Catastrophic,
II – Critical,
III – Marginal,
IV - Negligible

The first FMECA enhancement is that failure mode symptoms have been added to the "effects" column and are shaded in blue (or light gray). Failure mode symptoms are events that can be observed prior to the failure mode occurring or when the failure mode is in a very early stage of development. Subsequent effects may or may not be downstream failure modes. In the case where an effect is a downstream failure mode, the failure mode of focus could be considered a failure mode precursor.

The "Component" column identifies the component immediately affected by the failure mode while "Module" is the subsystem in which the component resides. This functional relationship is cross-referenced with the functional block diagram. In a similar fashion, the "Sensor" column lists the sensor that can observe the symptom or effect while "S_Module" is the subsystem in which the sensor resides and "S_Component" is the component it is linked to. All sensors in this example are required for control or safety purposes. Finally, "Diagnostics" and "Prognostic" column have been added. The "Diagnostics" column describes if there are any discrete diagnostic (Built in Test (BIT)) or continuous processing algorithms that can observe the symptom or effect. The "Prognostics" column describes any prognostic algorithms that can be used to obtain a RUL prediction on the failure mode.

6. RESPONSE MODELS

In some cases, a model of a subsystem may be developed that can provide valuable insight into where sensor are likely to have the most observational quality on failure modes. This optional level of fidelity allows for detailed, physics-based subsystem modeling, to be used for examining PHM trade-off's. Such tradeoff's at this level would include analyzing the number of sensors required, location of the sensors and associated algorithms. This type of model would be integrated in the overall HM design environment thus far discussed where cross-system influences can be examined and accounted for (Figure 5).
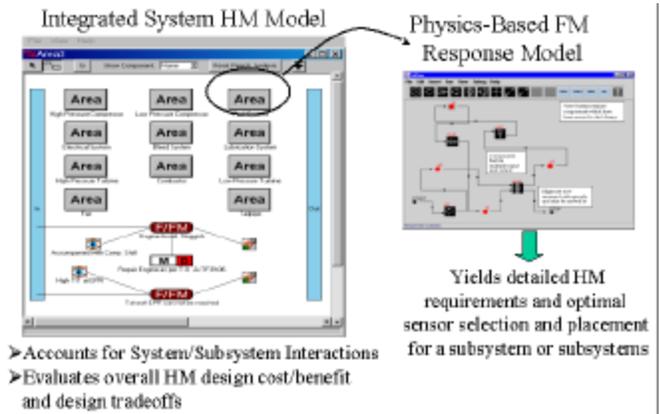

Figure 5 – Response model integration in the overall HM model

One such system response model for a hydraulic system developed by Dr. Jacek Stecki et al. of Monash University is shown in Figure 6. This model illustrates how the system model may be perturbed to simulate how the effects of certain modes propagate in time and space. Sensor / algorithm combinations can be examined for their ability to detect the perturbations.
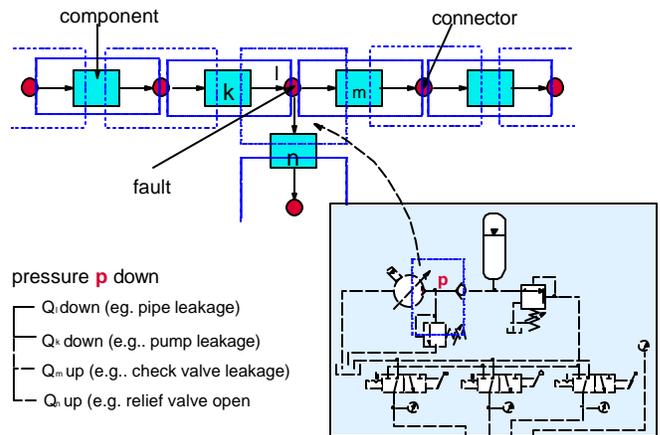

Figure 6 – Example of a detailed system response model

7. HEALTH MANAGEMENT ATTRIBUTES

To autonomously evaluate the cost/benefit of a HM system configuration, all aspects of the system must ultimately be assigned, or modify, a dollar value so that a cost function can be generated and optimized. Some of these "attributes" are more easily derived that others. The attributes assigned within a HM system and their respective icons are linked to Failure modes (F/FM), Sensors (eye), Effects, Diagnostics (Stoplight-discrete, x-y plot - continuous), Prognostics (stethoscope) and Maintenance Tasks (M). A short list of these attributes is shown in Figure 7. Some of the less obvious attributes are described next.
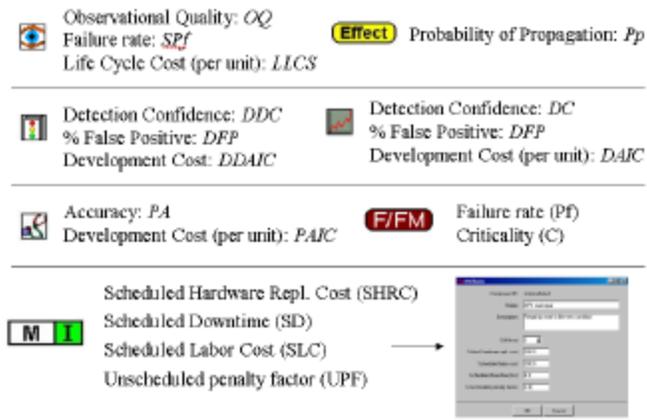
Figure 7 - Short list of HM attributes

Sensors

Sensors are defined in the model as components for measuring physical quantities such as temperatures, pressures and currents. The "Observational Quality" attribute of a particular sensor is a measure of the sensitivity with which it is able to pick up a physical signal linked to a particular failure mode. For example, an accelerometer stud mounted on top of a bearing casing may have a better observational quality than one magnetically mounted some distance away.

Diagnostic and Prognostic Attributes

Diagnostics can be either discrete or continuous. Discrete diagnostics are traditionally algorithms that produce 0 or 1 depending on if a threshold has been exceeded. Many types of Built In Tests (BITs) can be classified as Discrete Diagnostics. An example of a discrete diagnostics is an Exhaust Gas Temperature (EGT) reading that has exceeded a predetermined level.

Continuous diagnostics are algorithms designed to observe transitional effects and diagnose a failure mode based on the method and rate in which the effect is changing. Continuous diagnostics are usually associated with observing the severity of failure mode symptoms. Examples of continuous diagnostics would be a spike energy monitor for identifying low levels of bearing race spalling or an A.I. classifier for diagnosing that a valve is sticking. The "Detection Confidence score (0-1) – (DDC)", and "% false positive score (0-1) – (DFP)" can be used to simultaneously account for true-negative and true-positive characteristics.

Finally, Prognostic algorithms can use a combination of sensor data, a-priori knowledge of a failure mode and diagnostic information to predict the time to a failure or degraded condition with confidence bounds. Prognostic algorithms are linked directly to failure modes in the graphical FMECA model.

Prognostics do not have an attribute associated with false alarms. The "Prognostic Accuracy" accounts for the early

detection quality of the technology. A physical prognostic model (i.e. based on an FE model) would ideally have a higher prognostic accuracy than an experienced-based model (i.e. Weibull distributions of historical failure rates). More details on model fidelity are discussed in [2].

A valid concern is how the technical attributes of diagnostic and prognostics technologies can be determined. One method is addressed in [1], whereby algorithms are test objectively from performance and effectiveness standpoints using transitional run to failure data. Of course in the absence of this type of information, and with a new sensor/algorithm combination, an educated guess may be the only option.

8. COST FUNCTION

The health management design environment configuration and attributes contain a sufficient amount of information to generate and evaluate a "fitness" function. This fitness function is of the form:

For each Failure Mode – FM(i)
*Step 1)   Probability of Failure * Severity *Consequential Cost of FM(i) +(Downstream Failure Mode Consequential Costs) * Probability of Propagation*
*Step 2)   *HM risk reduction attributed to FM(i)*
Step 3)   + Cost associated with False Alarms on FM(i)
Step 4)   + Total Cost of all HM technology

The Consequential Cost (CC) is the sum of the direct and indirect costs required to address a particular fault/failure mode (i.e. repair, replace, inspect) ranging from quantifiable repair and labor costs, to less concrete costs such as the effect on system availability. Clearly, only a small aspect of all the possible factors are addressed here and the issue is purposely left ambiguous. If the probability of failure multiplied by consequential costs is defined as risk, health monitoring reduces risk by providing a probability that a particular failure mode can be prevented by 1) either detecting an "upstream" fault/failure mode or 2) prognosing when a fault/failure mode will occur. Unfortunately, the health monitoring adds development and hardware costs as well as the potential for false alarms. At the system-wide level, the benefits of the health monitoring technologies in terms of risk reduction must offset the costs and risk of the technology addition.

Specifically, the formulation is as follows (using the acronyms defined in Figure 7):

Steps 1 and 2 =

$$\sum_{FM_i}^{FM_N}\left\{\left[\prod_{D_{jd}}DC\cdot\frac{\sum_{S_D}OQ(1-SPf)}{NsensorsD}\cdot\prod_{P_{jd}}PA\cdot\frac{\sum_{S_P}OQ(1-SPf)}{NsensorP}\right]\cdot\left[(Pf\cdot S(CC-M)\cdot Pp)+\sum_{FM_{i+d}}^{FM_q}Rolled\_Up\right]\right\} \quad (1)$$

The "Rolled Up" costs =

$$Pf \cdot S(CC) \cdot Pp \cdot \left(\prod_{D_{FM}} \left(1 - \frac{\sum_{S_{FM}} OQ}{NsensorsD} \right) \cdot DC \cdot \prod_{P_{FM}} \left(1 - \frac{\sum_{S_{FM}} OQ}{NsensorsP} \right) \cdot PA \right) \quad (2)$$

Step 3 =

$$+ (1 - Pf) \cdot S \cdot \left[1 - \left[\prod_{S_{FM}} (1 - SPf) - \prod_{D_{FM}} (1 - FP) \right] \right] \cdot CC \quad (3)$$

Finally Step 4 =

$$+ \sum_{S} AIC + \sum_{D} DAIC + \sum_{P} PAIC \quad (4)$$

HM Design Optimization

The goal of the HM system optimization is to maximize the risk reduction provided by the design while minimizing costs. The optimization of the previously described cost function will operate between two boundaries; a "maximum" HM system configuration that includes the "wish list" of all potential sensors and associated algorithms that achieve complete failure mode coverage and a "minimum" configuration that is necessary for safety and control. The optimization algorithm will examine random configuration variations and calculate the "fitness" or cost for each.

A genetic algorithm optimization scheme was chosen for the HM optimization because genetic algorithms are better configured to handle optimization problems with little regard for non-linearity, dimensionality or function complexity in general. Potential cost functions generated in the HM environment can include hundreds of independent variables and thus makes it impractical to utilize traditional optimization techniques such as gradient decent or other derivative-based algorithms. While the details of the optimization are outside the scope of this paper, it is important to note that there will be no clear "winner," rather many different HM system configurations will be suggested that the designer can evaluate on the basis of additional criteria. More on this subject can be found in [7].

9. COLLABORATIVE DESIGN ENVIRONMENT

Before an example is given, it is important to address the design environment and associated architecture to enable the entire process. A collaborative work environment is being implemented in this program to allow a number of domain experts to operate applications from different locations, potentially on different operating systems, while sharing and maintaining the same data. For instance, the HM Design Tool will be used to perform advanced component simulation models, FMEA and Cost/Benefit Models simultaneously at various locations. By utilizing the Internet

and standard data formats such as XML, data and applications will be accessible individually through web-based servers, and managed through an integration layer, which will control the communications protocol and access privileges (Figure 8).
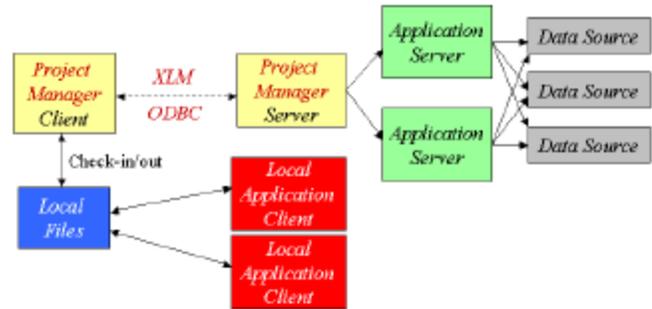

Figure 8 – Design of Collaborative Work environment

10. HM DESIGN EXAMPLE

A simple, yet realistic example of a Health Management design evaluation is shown next. In this example, an electrically actuated control valve concept is addressed for an aerospace application. Recall that a HM design model has many hierarchies ranging from the component level to the system level. For brevity, this example will consider, but not illustrate, the far-reaching system effects of various valve failure modes. The cost function for this model should by no means considered complete. The purpose of the example is only to introduce the HM design and optimization process.

The top portion of Figure 9 shows a Line Replaceable Unit (LRU) level Functional model of a Load Control Valve (LCV) that is used to regulate discharge air from an Auxiliary Power Unit (APU). Compressed air from the APU is used for main engine starts, environmental control and several other functions. The "in" and "out" bars on the left and right of the model are used to propagate signals, flows, and effects between levels.
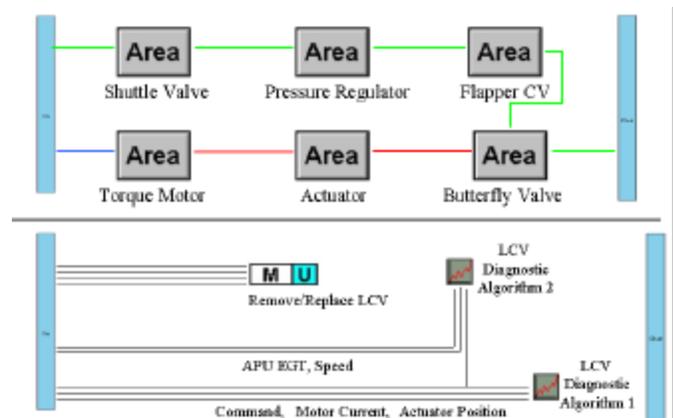

Figure 9 – Functional Model and HM design for LCV

The bottom portion of Figure 9 shows the unit level maintenance task (denoted by the "U") to remove/replace the LCV. Also shown are the *candidate* health monitoring algorithms that have the potential to detect a valve degrading in performance and allow for proactive maintenance. Algorithm #1 trends the relationship between LCV command, motor current, and the actual actuator position. In this scenario, the LVDT used to monitor the actuator position is a *candidate sensor*. Algorithm #2 trends the APU's exhaust gas temperature and speed with respect to the LCV command. All the sensors used for Algorithm #2 are available for "free" because they are required for control purposes.

Figure 10 shows the HM design at the torque motor level. Contained at this level is a failure mode of torque motor, the effects of such a failure, and maintenance tasks on the motor. Also shown is an existing Built-In-Test (BIT) based on the torque motor current. This BIT is either 0 or 1 and can provide *no* prognostic capability or truly isolate a failure mode.
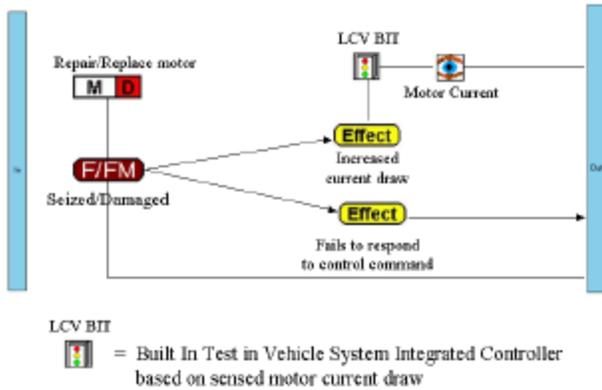

Figure 10 – HM design at the Torque motor level

Figure 11 illustrates the HM design at the actuator where the LVDT would physically exist. Note that due to the cause and effect relationship, failure of the actuator position to function could be the result of a torque motor problem or an actuator failure mode. Finally, Figure 12 is the HM design for the butterfly valve. Many upstream failure modes can cause it to malfunction creating potentially creating more critical downstream failure modes such as insufficient avionics cooling, inability to start the main engines, etc. Clearly, such a model should continue through system interactions until end effects are reached.
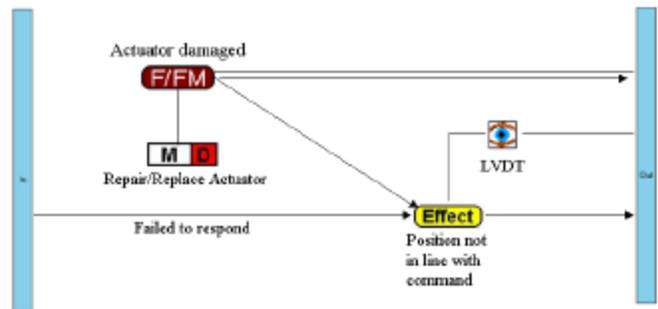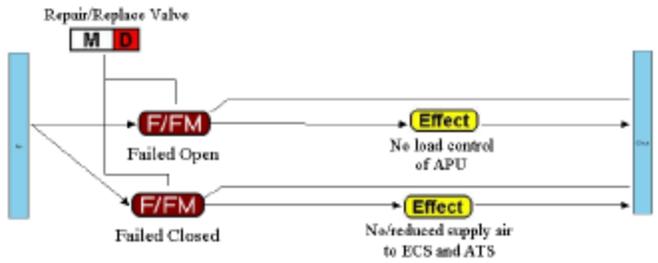

Figure 11 – HM design for Actuator

Figure 12 – HM design for Butterfly valve

Figure 13 provides a concise illustration of some of the attributes assigned to the HM elements in Figures 9-12 that were used in evaluating the cost function. Other "expensive" fault/failure modes such as inability to start the main engines and inadequate avionics cooling were also included. For brevity, the details of the cost function analysis will not be given. In this simple study, the LVDT sensor and algorithm #1 where found *not* to provide enough risk reduction for the cost, rather, algorithm #2 should be implemented. There are, of course, a number of variables contributing to this result the most dominent being the fact that algorithm #2 uses existing sensors even though it provides lower diagnostic confidence and was assigned higher development costs.

Figure 13 – Costs and probabilities for the HM design

11. Conclusion

An approach has been presented that extends traditional FMECA and system modeling capabilities to aid in the design of complex health management systems. This approach utilizes a graphical and collaborative design environment where failure modes, failure mode symptoms/effects, sensors, and diagnostic/prognostic technologies are represented. The health management system configuration can be optimized from a cost/benefit through analysis of the fitness attributes on HM system building blocks. The ultimate objective of this approach was to form a methodology and environment which enables effective health management practices by mitigating or preventing failure modes while still keeping sensor and diagnostic/prognostic technology costs at a minimum.

Acknowledgments

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